Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 91 (2016) 65 – 74

Procedia Computer Science

Information Technology and Quantitative Management (ITQM 2016)

Design of a decision-making tool to identify cross-correlation brain dominances

Felisa M. Córdova[a,*], Natalia Troncoso[b], Hernán Díaz[b], Fredi Palominos[c], Lucio Canete[d]

[a]School of Engineering, Faculty of Engineering and Business,
University Finis Terrae, Av. Pedro de Valdivia 1509, Santiago 05600002, Chile
[b]Faculty of Engineering, University of Santiago de Chile, Santiago 0560002, Chile
[c]Faculty of Science, University of Santiago de Chile, Santiago 0560002, Chile
[d]Technological Faculty, University of Santiago de Chile, Santiago 0560002, Chile

Abstract

The objective of this study is to design a decision-making tool to carry out a sequence of intermediate processing analytic steps in order to render a graphic visualization of significant correlations between pairs of EEG channels. We submitted a set of students to an abbreviated version of a visual intelligent test while we recorded EEG activity covering frontal, temporal, parietal and occipital areas of the brain cortex through the scalp. The graphs generated show correlations between specific ranges of R Spearman values and pairs of electrodes relevant for the particular study needed. We used this tool to make a descriptive classification of subjects according to the inter-channels correlation maps generated by our decision-making tool. We called correlation “dominances” to the areas defined for a high concentration of significant correlations. This term has been used previously as a way to classify styles of people’s thinking-acting in relation to four descriptive referential brain areas. We contrasted our correlation dominances results with this psychological-questionnaire tool in search of consistencies. To design the brain connectivity module, we used Rapid Application Development (RAD) methodology. The tool has been developed in Matlab to analyze signal data ranges delta, theta, alpha, beta, and gamma; all these obtained from the EEG cleaned off artifacts, pre-processed and separated into bands using EEGLAB. Pearson correlation is utilized to detect synchronic connectivity dominances (correlations) through the brain areas. The results are presented in terms of cross-correlation maps, or correlation matrices, between the 14 channels of EEG signal for different EEG frequency bands.

Peer-review under responsibility of the Organizing Committee of ITQM 2016

Keywords: decision-making tool; brain dominances; EEG; Matlab; linear correlation

* Felisa Córdova Tel.: +56-02-23260268; Fax: +56-02-23260268.
E-mail address: fcordova@uft.cl

Peer-review under responsibility of the Organizing Committee of ITQM 2016
doi:10.1016/j.procs.2016.07.042

1. Introduction

The analysis of physiological data has revealed a lot of information about the functioning of the human being which is complexly composed by an interrelated system of organs which are alongside sub-systems and sub-organs of other systems [1-3]. At the same time that data acquisition technology and storage capacity has expanded their territories, the need to deal with the enormous amount of recordable and already recorded data containing valuable hidden information stimulate data science to find new supporting technologies and/or procedures to accelerate the rate of data-analysis that data scientist can perform, in terms of data mining and data visualization [4-5]. A permanent effort for finding patterns in the world around us has been always the pursuit of science: to discover the hidden codes that build up the language of nature. To do this, it is needed to put those hidden patterns in codes we human beings are able to decode and understand [6-8]. One of our preferred codes is visual and it helped us to understand through visualization the relationships that two or more variables have in common. There are a good number of general and specific applications for data visualization but for more specific purposes is always needed the development of custom-made tools [6-9]. In the realm of physiological data analysis one of the most challenging phenomena to deal with is that of the brain functioning behavior, the multivariable phenomenology here implied makes difficult to visualize many things at the same time [10-14].

Considering that the process under study is an ever going phenomena, a time dimension cannot be simply collapsed to have an average behavior statistically valid but artefactual in terms of that only reveals a central tendency when what we are really interested is in the temporal variation of this behavior around any central tendency. Furthermore, when using EEG data we are dealing with samples rates that go from128 to > 300 Hz, so the temporal dimension can be subjected progressively to a more deep resolution analysis being able to find different behaviors at different time-scales or frequency ranges [15].

When looking at EEG as a *proxy* indicator of the brain functioning, one of the most attended characteristics of the brain operating have to do with the degree of correlation or anti-correlation between close or distant areas of the brain. It is understood that when neurons or groups of neurons are synchronically coupled, they are doing something together. In the sleep stages predominate Delta oscillations with a frequency range of 0.1 to 4 Hz. Then, higher frequency ranges or bands are correlated with a growing in awareness state. In slow wave sleep, waves other than delta waves are sparse, but during waking, a strong digital cacophony coming from other frequency ranges like theta, alpha, beta, and gamma, hide the always constant slow wave trains [15-16].

It is also understood that the higher the amplitude of the signal the higher the degree of synchrony between concomitant signals. By mean of this synchrony is that it is allowing its summation. By the contrary, when the brain starts to awake and different parts of its surface are required to perform different and more specific tasks, like perceptual or cognitive, brain de-synchronizes and the amplitude of the signal decrease in a $1/f^{\alpha}$ function in an amplitude v/s EEG frequency plot.

There is a lot of information underneath the surface of data points recorded and stored as a file so automatically assisting systems to perform different levels of data diving and search for patterns are very welcomed. To expand the experience of understanding data and emerging patterns it is necessary a visual tool of intercommunication, so data and pattern visualization is also a required and much-needed tool to complement with data mining. To have a clearer description of the different but simultaneous temporal domains in the EEG functioning, interacting among and between them, we design a tool to carry out a sequence of processes ending with the generation of functional correlation maps depicting the time-space dominant areas of high R Spearman correlation values between pairs of electrodes out of 14 EEG channels recorded from the scalp.

2. Decision-making Tool Model

The tool is composed by four sequential modules through which evolve EEG data processing from raw signals to organizational depicting graphs as shown in Fi. Here, the organization is referred as a degree and topology of signal cross-correlation between pairs of EEG channels, but it is possible to define other ways to contrast different sources of data.

2.1. EEG Signal Acquisition Module

The first module of signal acquisition is composed by a hardware and software which takes the brain signal and transform it into a digital signal at 128 or 256 Hz sample rate. The process involves a Fourier Fast Transform and a final export of the data with the .edf extension (European Data Format). This process can be allowed by any electroencephalograph. We used the brain-computer interface and scientific contextual EEG EMOTIV EPOC® to obtain the sequence of data coming from 14 locations of the scalp and, by extension, from the brain cortex, referred to the standard 10/20 EEG channels location system.

2.2. Filtering and Artifact Cleaning Module

The second module corresponds to the Matlab © EEGLAB Toolbox, which is an Open Source toolbox that allows to work with .edf type extensions, and other formats used in the sampling of EEG signals. The filters that are applied in EEGLAB are ADJUST filter [16] which removes gross artifacts and perform independent component analysis (ICA) to detect common artifacts. In this module, there is a need for a supervising user to check out visually and graphically the art factual components suggested by ADJUST and discard type I and type II errors. Many tools and visualizations provided by EEGLAB can help doing this. It is recommended the visual analysis of the independent components time development, the homogeneity of the relative intensity of the signal for all the channels and the 1/*f* shape of the intensity v/s frequency spectrum plot.

2.3. EEG Frequency Bands Division Module

In the third module, a frequency band EEGLAB filtering is included to split apart the brain electrical activity into five standard frequency bands:

- Delta frequency]0,4[Hz .: Sleepy, dreaming
- Theta frequency [4, 8[Hz.: Drowsy, meditative
- Alpha frequency [8, 13[Hz.: Relaxed, reflective
- Beta frequency [13, 30[Hz.: Alert, working
- Gamma frequency [30, + [Hz.: Active thought

This separation of frequency ranges depends on what you want to analyze, what it is looking for in the EEG, or what the process you want to study. Different frequency bands imply different velocities at which things happen in the brain.

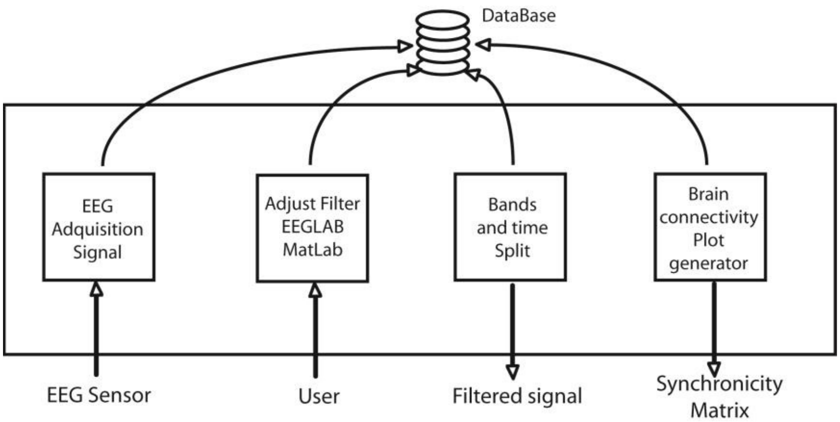

Fig.1. Decision-making tool modules

2.4. Cerebral Dominances Connectivity Module

This module allows the calculation of the matrices of correlation of the EEG signals by bands at a time interval and the generation of connectivity graphs indicating the subject's brain inter-channel cross-correlation dominance. The application developed for this module considers the Rapid Application Development methodology (RAD). The RAD methodology basically consists of a cycle of software development designed to achieve a high-quality result, as with traditional forms of development application in shortest time. It has an incremental character since with each cycle improves the system that the process is creating. It also involves the user in the development process by the need to evaluate the outcome of each cycle [17].

The first stage sets out the requirements of the system, laying the necessary groundwork for the development. The second stage includes the design of the prototype, where the forms are created to meet the requirements previously set. Then, it enters the phase of building the prototype based on the design of the previous stage to continue with the evaluation of the functionality of the system by the user and developer alike. In case evaluation is not satisfactory, the system comes back to the design stage to solve problems found and repeat the cycle until a satisfactory evaluation is obtained.

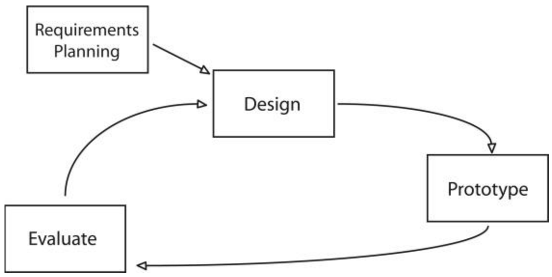

Fig.2. Rapid Application Development Methodology (RAD)

In this case we use 3 'primary' steps in which models are made, then move to the last 2 steps which consist of the application and then perform the necessary tests to the prototype, iterating until you reach a final prototype [17]. Since Matlab © is a powerful calculation engine, it is used as a platform for this application programming. The Graphical User Interface (GUI) are here used to give the user an easier environment and thus subsequently set the functionality of each of the objects within the interface.

Reports delivered by this module correspond to the maps of correlation for each one of the bands of frequency at predetermined times, where it is possible to distinguish high and negative correlations also, as well as areas of the cerebral cortex that show greater connectivity or the hemispheres where it occurs. This analysis allows us to identify a possible relationship between already proposed systems of people's classifications based on psychological tools but phrased with a brain-derived outfit.

3. Experimental Design and Results

3.1. Sample

The sample used corresponds to 20 students from different levels of civil engineering and engineering in industrial implementation of the University of Santiago of Chile, of both sexes and between 18 and 26 years.

3.2. Raven test

Since intelligent test are an accepted tool frequently used in the estimation of the intelligence quotient (IQ), a simple abbreviated version of an intelligence test was chosen. The full version test is known as Raven's progressive Matrices, and has many advantages for using in exploratory studies. First, it is a test of a generic nature, i.e. is independent of age, sex, language and culture of the individual [18–19–20–21]. The test consists in to select, from a number of given alternatives, the figure or pattern that fits as the *missing one* in a context of a number of given patterns which hide an underneath logic of construction and spatial disposition. Figure 3, shows one example of the presented matrices where subjects must choose an alternative while analyze a contextual image in which to fit it. The subject must choose one out the eight choices below to match with the pattern presented.

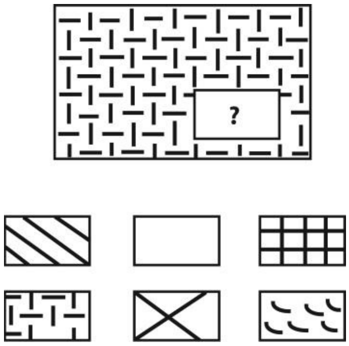

Fig.3. A sample of Raven's matrix

The version of the test of Raven used in testing students was an abbreviated version of 15 questions, which are divided into three groups of five questions, with a progressive increase in difficulty. The Raven test is an objective test since it is made from images that do not necessarily evoke a feeling and which therefore oblige the person who is solving it to think logically and reason by analogy in order to find solutions to each question.

3.3. Brain dominances by mean of a psychological test

We tested classical psychological Herrmann's brain dominances by mean of a questionnaire and contrasted these results with the map of EEG correlations generated by the brain while performing a logical visual intelligent task [12-13]. We expect this provide an objective and quantitative tool to study people according to the way their brains process and solve cognitive challenges. Also, this allows us to use the tool to extract valuable information from data about how some brains reorganize their processing resources to deal with challenging environments that require analytical and logical thinking. We finally explore the potential relationship between, apparently successful psychological tools, built to determine predominant brain processing and behavioural components of people, with a quantitative data mining and data visualization procedure which renders maps of EEG channels highly cross-correlated during the intelligent test solving.

Students meet the test of Herrmann's Brain Dominances in its reduced version, which will allow us to contrast the results of the application. This test is based on understanding the brain as divided into 4 different quadrants, attributing to each of these quadrants specific characteristics in the way of people process information. Thus, the test renders four different percentages that correspond to how dominant is the part of the brain, these parts are upper left (to be rational), top right (be Experimental), bottom left (be careful) and bottom right (being emotional).

3.4. Procedure testing

To put into a test the procedure here proposed, we recorded the EEG of 20 students while solving an abbreviated (15 questions) version of the Raven's progressive Matrices test. In this form of the test, there is an increase of difficulty through the sequence of questions and a sudden increase of difficulty for the questions 10 to 15. We obtained high synchrony ($R>0.8$) functional connectivity maps for all subjects and for the time spent in solving each of the 15 questions. Figure 4 shows the cross-correlation matrix obtained after apply Spearman correlation between pairs of channels. We choose to depict interconnecting lines over the map of electrodes position on the head when Spearman $R>0.8$.

	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
AF3		-0,0358	0,297	0,0322	0,125	-0,053	-0,2898	0,3699	0,5375	0,427	0,345	0,4432	0,6193	0,2694
F7			-0,0437	0,937	-0,8171	0,1023	-0,2466	-0,4478	-0,0944	0,1224	-0,4856	-0,3609	-0,7016	-0,6274
F3				-0,2547	0,3202	-0,1999	-0,359	0,2131	0,1063	0,1565	-0,0452	0,3355	0,2498	0,1599
FC5					-0,8712	0,0622	-0,2785	-0,5667	-0,2179	-0,017	-0,3531	-0,2339	-0,6405	-0,5795
T7						0,2812	0,5284	0,6189	0,1718	-0,1546	0,0412	0,2411	0,4725	0,2541
P7							0,797	0,4971	0,2416	0,0063	-0,7988	-0,0458	-0,3814	-0,4033
O1								0,3828	0,0671	-0,2646	-0,5273	-0,3674	-0,2941	-0,4178
O2									0,827	0,6131	-0,0907	0,3038	0,5073	0,4423
P8										0,9107	0,1004	0,0896	0,4946	0,4066
T8											0,1459	0,1163	0,4011	0,4732
FC6												0,2016	0,7689	0,6585
F4													0,5519	0,6534
F8														0,8433

Fig.4. Cross-correlation Matrix between pairs of 14 EEG channels

Figure 5 shows the functional connectivity maps of dominances based on highly synchronic (R>0.8) pairs of electrodes generated by the implemented tool. The figure depicts the functional synchronic patterns of 5 subjects during solving the first five questions of the abbreviated Raven´s test.

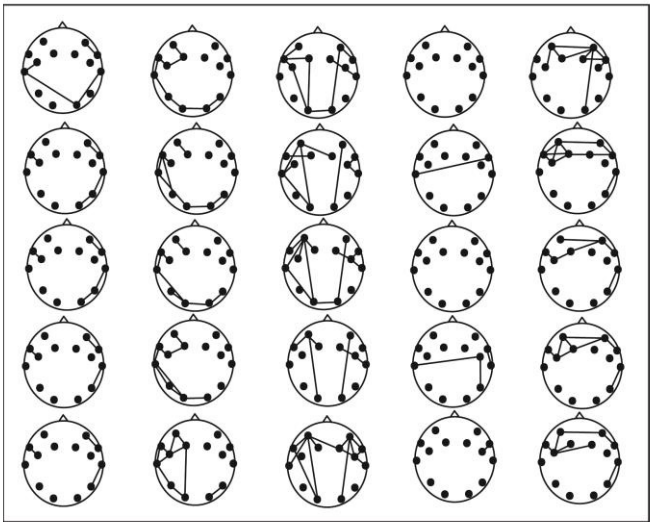

Fig.5. Functional connectivity maps of dominances (questions 1 to 5)

Different patterns of cross-synchronicity are observed along the solving process with a certain degree of pattern constancy through the first 5 questions. Subjects KO and FL show few pair of channels highly correlated, while the other three subjects keep a relatively high number of significant (R>0.8) inter channels cross correlations active during the whole experiment.

Table 1 shows individual differences and consistency in the amount of highly correlated pairs of EEG channels during the test´s solving process. It corresponds to a descriptive statistic of the number of r > 0.8 cross-correlations by subject (representative sample n=5) along the whole solving process of the abbreviated raven´s 15 questions.

Table 1. Descriptive statistic along the whole solving process of the abbreviated raven´s 15 questions

Descriptive statistic of R > 0.8 cross-correlations by subject	KO	AR	CVM	FL	TM
TOTAL	5.8	99	131	26	111
AVERAGE	3.87	6.6	8.73	1.73	7.4
S.D.	0.77	3.23	2.29	1.41	2.66

Figure 6 shows the functional connectivity maps of dominances based on highly synchronic (R>0.8) pairs of electrodes generated by the implemented tool. The figure depicts the functional synchronic patterns of 5 subjects during solving questions 11 to 15 of the abbreviated Raven´s test.

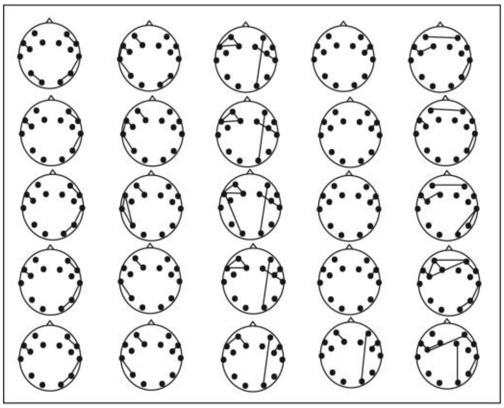

Fig.6. A representative sample of five individuals during the resolution of questions 11 to 15 questions

Considering only the three subjects of this sub-sample that has high averages of significant cross-correlations along the whole experiment (subjects AR, CVM and TM), it is possible to see the tendency to the reduction in the number of cross-correlated pairs of channels through the evolution of the test.

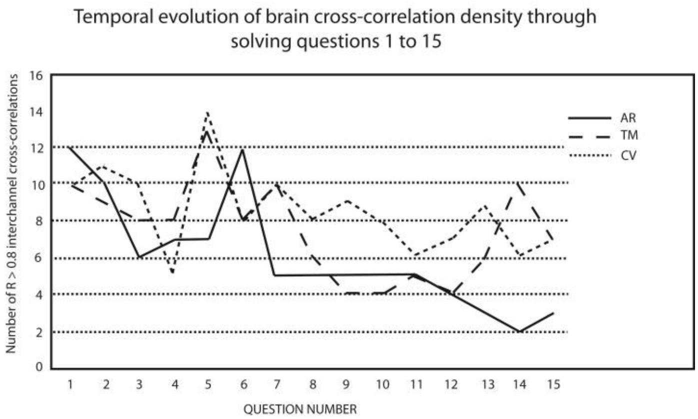

Fig.7. Temporal evolution of the decreasing number of cross-correlated pairs of EEG channels

As expected, while increasing the complexity of the problem, some brain use the strategy to desynchronize and divide to conquer. Figure 7 plot this reduction in the density of highly correlated areas through solving the test for the three subjects selected from the sub-sample with high averages of cross-connections to be able to see a trend.

Negative linear trends for the three subjects are expressed in the equations of the graph. Figure 8 shows the temporal evolution of the decreasing number of cross-correlated pairs of EEG channels (electrodes) along the whole process of solving 15 questions of Raven´s abbreviated version test. Table 2 shows the results of the Herrmann's Brain Dominances test in its reduced version for the 5 subjects selected.

Table 2. Results of the questionnaire to estimate Herrmann's Brain Dominances

Herrmann´s Dominance by Questionnaire	A	B	C	D
FL	39	36	33	31
KO	32	35	34	33
AR	25	35	43	35
TM	33	34	31	34
CVM	43	29	29	30

According to Hermann`s brain dominances classification results for the five subjects chosen as an example in our study, it is possible to note that they are very symmetrical in the way they use or prefer the thinking and processing characteristics of the four quadrants defined by the test: A = upper left (Rational and Analytics); D = top right (Experimental and Unpredictable); B = bottom left (Order and Organized); and C = bottom right (Feelings and Emotional). Figure 9 shows the superposition of the Herrmann's brain dominances for subject TM (according data showed in Table 2) indicated by the central polygon of the prevalence of thinking and assumed brain procedural operation, with the cross-correlation (R>0.8) map rendered by our procedure (black dashed lines connecting electrodes positions). This procedure renders much more information about brain processing of the brain of subject TM while answering question number 6. While Herrmann`s classification gives a rather symmetrical predominance along the four quadrants, our visualization gives more specific details about which areas of the brain appears high cross-correlated, which in this case are mainly located at the left and right frontal areas in Figure 8.

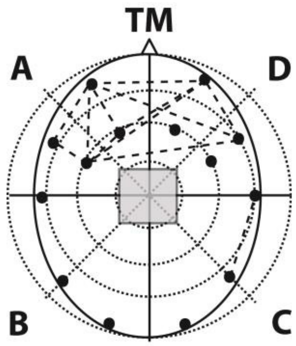

Fig.8. Superposition of the Herrmann's brain dominances for subject TM (according with Table 2)

4. Conclusions

Pattern recognition and the organization of these patterns has been a fundamental tool in the cognitive evolution of animals and humans. While any new recently born living being needs to setup and tune with the environment, a corresponding structural and functional coupling between the organism and the environment occurs. So in a very fundamental way, happens that the organism and the environment that surrounds it must reflect each other as an inverse image of themselves. In such a way, when we study one of them we are also studying the other.

This approach avoids the cause-effect quest and redirects the focus on variables that in one way or another be direct, or proxy ways, to know something about the functional identity of the phenomenon.

Detecting patterns in a phenomenon means that there are some regularities in it that are useful when we are interested in to explain how order appears from a noisy and uncorrelated background activity.

This self-similarity gives us the sense of a purpose, of a goal, but in considering evolution as a non-purposeful natural experiment, that only renders thermodynamically possible outputs, the autocorrelation fingerprint reflect not purpose, but self-organization.

Visualization of this self-organization can be understood as depicting different ways to see and understand the functional dynamic interface between organisms and medium. By having a visual representation of the temporal and topological trajectory of a multivariate dynamical system we can better understand its range of variability, its regularity, its persistence or its volatility.

Data mining and data visualization are made to unveil previously hid data information through the help of assisted data processing and automated or semi-automated processing devices to obtain knowledge through finding and depicting patterns from a set of big data.

We choose electrophysiological data (EEG) to test a decision-making protocol built to identify cross-correlation brain dominances based on a set of 14 channels (electrodes) placed on the scalp of 20 subjects.

The method chained a sequence of procedures starting with raw EEG data until to render a set of maps of inter-channel cross-correlations according to a specified range of R Spearman values.

The designed software allows standardizing the process of cleaning, filtering and analyzing EEG data according to custom initial parameters set by the user. This helps to a better control and standard procedures for managing several instances of analysis performed by different users, along with saving neither a lot of neither time neither compared with previously nor chained nor semi-automated or manual methods.

The system specializes in to calculate the cross-correlation of cortical brain areas of people faced to a brief visual intelligent test, but equally useful for a variety of experimental procedures interested in intra- and inter-individual comparison among a number of subjects.

In terms of diagnostic tool, the possibility to visualize different subjects and different frequency band's configurations of cross-correlation maps allow to the expert a new way to compose a diagnose in terms of the visualization of different temporal scales of analysis, according to the frequency bands that are chosen to perform the study.

The next step in the design of this prototype consists in the incorporation of new electrophysiological sensors to capture other than EEG physiological variables, which in a complementary way with the former, will allow us to analyse and visualize extended patterns of body-mind(brain) cross-correlations by connecting this EEG data with concomitant and coexisting on going emotional variables.

To help to standardize procedures and as a training tool for non-experts, we want to incorporate a learning machine system that analyse the set of decisions made by the visual inspection of trained eyes. As a training arena, this assisted decision-making tool will use the set of previously human (expert eye)-assisted decision-making step. At this stage, a very useful tool for new practitioners is the assisted advice to detect type I and type II errors, especially in deciding art factual components of the raw EEG signal.

Finally, an intelligent and friendly computer-user interface will allow integrate custom variable's initial conditions for the analysis and the specification of bandwidths in consideration. A module to visualize temporal evolution of inter-connectivity patterns as a sequence of images with a user-defined framerate progression will depict a more realistic on the go dynamic of a multivariate and complex system as the brain, allowing a better comprehension of the functional space of variability and regular short and long memory attractors of biological dynamical systems.

Acknowledgements

This work was supported by Universidad Finis Terrae and Universidad de Santiago de Chile.

References

[1] Sperry R. Lateral specialization of cerebral function in the surgically separated hemispheres. Mc. Guigan FJ editors. *The Psychophysiology of the thinking*, New York: Academic Press; 1973.

[2] Gazzaniga M. The cognitive neurosciences. MIT press; 2004.

[3] Sperry R. Split-brain approach to learning problems. New York: Academic Press; 1967.

[4] Córdova F, Díaz H, Cifuentes F, Cañete L, Palominos F. Identifying problem-solving strategies for learning styles in engineering students subjected to intelligence test and EEG monitoring. *Procedia Computer Science* 2015;**55**:18-27.

[5] Cincotti F et al. Non-invasive brain–computer interface system: towards its application as assistive technology. *Brain Research bulletin* 2008; **75**:796-803.

[6] J. Liu, J. Sun, S. Wang, "Pattern Recognition: an overview," International Journal of Computer Science and Network Security, vol. 6, 2006.

[7] Shi LC, Lu BL. Dynamic clustering for vigilance analysis based on EEG,2008, In: Engineering in Medicine and Biology Society, EMBS 2008. 30th Annual International Conference of the IEEE, Vancouver, British Columbia, Canada; 54-57.

[8] C. Kayser, "Listening with your eyes," Scientific American Mind, 2007 vol. 18, no 2, pp. 24-29.

[9] Kannon T, Inagaki K, Kamiji NL, Makimura K, Usui S. PLATO: Data-oriented approach to collaborative large-scale brain system modeling. *Neural Networks* 2011; **24**:918-926.

[10] Herrmann N. Creative problem solving; 1995.

[11] Herrmann N. The Creative Brain. *Training and Development Journal* 1981;**35**:10-16.

[12] Kashefi H, Ismail Z, Yusof YM. Supporting engineering students' thinking and creative problem solving through blended learning. *Procedia-Social and Behavioral Sciences* 2012;**56**:117-125.

[13] Bunderson CV. The validity of the Herrmann Brain dominance instrument. *The creative brain* 1989;**1**: 337-379.

[14] Ho KT, "The Dimensionality and Occupational Differentiation of the Herrmann Brain Dominance Instrument", Department of Educational Psychology, Brigham Young University;1988.

[15] Sokhadze TM, Cannon RL, Trudeau DL. EEG biofeedback as a treatment for substance use disorders: review, rating of efficacy and recommendations for further research. *Journal of Neurotherapy* 2008;**12**:5-43.

[16] Mognon A, Jovicich J, Bruzzone L, Buiatti M. ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features. *Psychophysiology* 2011; **48**: 229-240.

[17] Martin J. *Rapid application development*. New York: Macmillan publishing company;1991.

[18] Raven J. The Raven's progressive matrices: change and stability over culture and time. *Cognitive psychology* 2000; **41**:1-48.

[19] Kolb DA. Management and the learning process, *California Management Review* (pre-1986), 1976;**18**:3-21.

[20] Honey P, Mumford A. *The learning styles helper's guide*. Maidenhead, Berkshire: Peter Honey; 2000.

[21] Rashid, NA., Taib, MN., Lias, S., Sulaiman, N., 2010. "Classification of learning style based on Kolb's Learning Style Inventory and EEG using cluster analysis approach", Engineering Education (ICEED), 2010 2nd International Congress on. IEEE, 2010; 64-68.